ConvoNexus AI Using Google Meet with Multilingual Features

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Abstract: This paper presents an Advanced AI-Powered Google Meet System that integrates real-time speech recognition, intelligent summarization, multilingual translation, and contextual AI assistance into a unified web-based video conferencing platform. The proposed system enhances traditional online meeting environments by embedding a deep learning–driven conversational agent capable of extracting live captions, performing speaker-aware transcription, generating concise meeting summaries, and translating outputs into multiple languages to support global collaboration. The architecture combines WebRTC-based communication, DOM-based live caption extraction, RESTful backend services, and transformer-based natural language processing models to deliver scalable and low-latency performance. Additional modules such as automated meeting admission control, AI-driven action-item detection, sentiment analysis, and secure authentication improve meeting productivity and decision-making efficiency. Experimental evaluation demonstrates improved transcription accuracy, reduced summarization time, and enhanced multilingual accessibility compared to conventional conferencing tools. The system provides a cost-effective, scalable, and intelligent framework for next-generation virtual collaboration, making it suitable for academic, corporate, and enterprise environments.

Index Terms **- Artificial Intelligence (AI), Video Conferencing, Intelligent Virtual Assistant, WebRTC, Speech-to-Text, Natural Language Processing (NLP), Automatic Meeting Summarization, Multilingual Translation, Real-Time Caption Extraction, Sentiment Analysis, Meeting Analytics, Cloud-Based Architecture, Human–Computer Interaction (HCI), Transformer Models, Secure Authentication.**

I. INTRODUCTION

INTRODUCTION

The high rate of development of intelligent communication technologies has turned the classical video conferencing platform into the smart collaborative ecosystem. As remote learning and virtual meetings become more and more widespread, telemedicine, and distributed software creation, platforms like Google Meet are important digital infrastructure. Nevertheless, the traditional video conferencing platforms are mainly concerned with the real-time audio-visual communication, which does not provide much intelligent support in terms of automation, contextual assistance, and post-meeting knowledge extraction. To overcome these drawbacks, this paper suggests an Advanced AI Google Meet Assistant, a combined artificial intelligence system that will be used to improve the experience of the virtual meeting by providing real-time transcription, automatic summarization, multilingual translation, intelligent response generation, analysis of speakers, and automation of contextual tasks. The system takes advantage of current natural language processing (NLP) and deep learning algorithms and cloud-based application programming interfaces to convert raw meeting discussions into formal guided action insights.

The suggested architecture will use a secure authentication mechanism, AI-powered caption extraction, speech-to-text integration, semantic summarization, sentiment analysis, and interactive chatbot support in one integrated web-based interface. The platform enhances access and productivity and allows retaining knowledge and tracking decisions by incorporating AI modules in the meeting process. In addition, the system advocates multilingual communication, backend processing that is scalable and privacy conscious data handling systems, which is exploitable in academic, corporate and enterprise settings. The experimental assessment can prove the efficiency of the meeting, less manual documentation effort, and the user engagement of the traditional video conferencing systems. This study will help enhance the development of intelligent collaborative systems because it will bridge the technology of real time communication with adaptable AI-based automation.

NEED OF THE STUDY

The rapid growth of online collaboration platforms has transformed communication in academic, corporate, and enterprise environments; however, existing video conferencing systems primarily focus on audio-visual interaction while lacking intelligent automation and real-time cognitive support. Participants often struggle with note-taking, language barriers, information overload, missed action items, and inefficient post-meeting documentation. Additionally, traditional platforms provide limited capabilities for contextual understanding, sentiment analysis, multilingual accessibility, and automated knowledge extraction. With the increasing demand for remote work, global teamwork, and hybrid learning environments, there is a critical need for an AI-integrated meeting framework that enhances productivity, accessibility, and decision-making efficiency. Therefore, this study aims to design and implement an Advanced AI-Powered Google Meet System that incorporates real-time speech recognition, automated summarization, multilingual translation, intelligent meeting analytics, and secure cloud-based architecture to bridge these gaps and create a smarter, more inclusive, and data-driven virtual collaboration ecosystem.

II. ITERATURE REVIEW

In the recent past, improvements in Artificial Intelligence and Natural Language Processing (NLP) have played a major role in the creation of intelligent communication systems. Previous studies have investigated the deep learning frameworks of automatic speech recognition (ASR) in the form of Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), and Transformer structure as accurate speech-to-text decoders. Extractive and abstractive methods Automated text summarization studies have utilized attention-based sequence-to-sequence summarization models and existing pre-trained transformer models, e.g. BERT and GPT models, to generate short and informative summaries. Neural Machine Translation (NMT) Multilingual translation systems have also enhanced cross-language collaboration by encoder-decoder systems with attention layers. Also, sentiment analysis and conversational AI research have allowed understanding the context of meeting conversations. Nevertheless, the majority of the current video conferencing services combine all these features as a stand-off service and not as a real-time intelligent assistant and part of the meeting workflow. Thus, an all-encompassing AI-based conferencing system integrating live captioning, contextual summarization, multilingual support, and actionable analytics is an important void in the research that the study fulfills.

III. PROPOSED SYSTEM ARCHITECTURE

The Advanced AI-Powered Google Meet System proposed is created on the basis of modular, scalable, and layered architecture to provide real-time performance, security, and extensibility. The system comprises five main layers,

3.1 Client Interface Layer

The Client Interface Layer is created based on the React.js and current web technology to give a responsive and interactive meeting experience. WebRTC protocols enable real-time audio and video communication and enable peer-to-peer media streaming with a low minimum of latency. The system retrieves live captions of the Document Object Model (DOM) of the browser and at the same time retrieves audio streams to process the speech further.

3.2 Communication Layer

The Communication Layer supports the signaling mechanisms and encrypted media transmission via the use of secure WebSocket and HTTPS protocol. This provides good connectivity of the participants, authentication and meeting session control. The data obtained by extracting speech is passed with the help of RESTful APIs to the AI Processing Layer.

3.3 AI Processing Layer

The AI layer is used to combine transformer-based Automatic Speech Recognition (ASR) models that are used to perform transcription, abstractive summarization models that are applied to create summaries of meetings, Neural Machine Translation (NMT) modules used to generate multilingual output, and sentiment analysis classifiers used to identify emotional tone and the level of engagement.

3.4 Backend Service Layer

Back End Service Layer Back End is a layer that is being developed with the Django REST Framework that will be used to coordinate the API routing, user authentication, meeting storage management and to control secure access. The data exchange is implemented using the lightweight communication of frontend and backend in JSON format.

3.5 Data Storage Layer

Data Storage Layer draws on SQLite or clouds databases that safely store the transcripts, summary, translation result and the meeting analytics. The modular architecture is scalable and could be integrated with any new AI modules (action-item extraction, predictive analytics, and AI co-host automation) without having to redesign the overall system architecture.

The modern web technologies (React.js and WebRTC) are used to develop the client layer to provide the opportunity to communicate in real-time and exchange audio-video messages and the live captions based on the DOM. The communication layer deals with peer-to-peer connections and secure signaling to guarantee low latency communication. The speech data having been extracted is sent to the backend via RESTful APIs, and the AI processing layer uses transformer-based speech recognition models, summarization models, multilingual translation models, and sentiment detection models. The server, which is developed based on the Django REST Framework, does authentication and meeting organization, as well as the coordination of APIs, and transcripts and summaries are stored safely in SQLite or cloud databases. The architecture is scalable, secure, and modularly extendable to add more AI services like predictive analytics and automated item tracking to the architecture with ease.

IV. RESEARCH METHODOLOGY

The working methodology of the proposed system follows a structured pipeline from data acquisition to intelligent output generation:

4.1 Authentication of the user and initializing a meeting

The log-in of users to the system is based on the use of tokens. When a successful authentication is made, then a meeting session is launched and WebRTC creates real-time communication between participants, which is audio-video.

4.2 Real-Time Audio Capture and Caption Extraction

WebRTC APIs are utilized in recording audio streams during the meeting. At the same time, there is the extraction of live captions in the browser DOM as backup and better transcription. The captured speech signals undergo preprocessing in order to isolate background noise and equalize the level of amplitude.

4.3 Automatic Speech Recognition (ASR)

The audio signal has been preprocessed and sent to an ASR model that is deep learning based. The model translates speech signals into text transcripts through the acoustic modeling and language modeling methods. Transcription is tested with regards to Word Error Rate (WER). Transcription probability can be given mathematically as:

$$W* = \arg\max P(W|X)$$

where X represents the audio signal and W represents the word sequence.

4.4 Text Summarization

The transcript produced is inputted into a transformer-based summarization model which uses attention mechanisms to select sentences that are contextually important and produces a concise summary. The goal of the summarization can be presented as follows:

$$S=f(T)$$

where $T$is the transcript and $S$is the generated summary.
ROUGE metrics are used to evaluate summarization quality.

4.5 Multilingual Translation

In this step, the original content is multiplied using multiple languages. The processed text is a summarized and inputted into the Neural Machine Translation (NMT) module in encoder-decoder architecture with attention. Probability of translation is given as:

$$P(Y|X)=t=1⎡⎣nP(yt|yt−1,...,y1,X)$$

where $X$is the source language text and $Y$is the translated output.
BLEU scores are used to evaluate translation accuracy.

4.6 Sentiment and Action-Item Detection

A classification model is used to create a sentiment polarity (positive, neutral, negative) and identify statements that can be acted on based on a supervised learning approach on the transcript. This improves the encounter analytics and productivity tracking.

4.7 Generation of storage and analytics.

All the results of the processing are stored in the database, transcripts, summaries, translations, and sentiment scores. The system creates analytics dashboards (duration of the meeting, participation of the speakers, trends of sentiment, and critical decision points).

4.8 Delivery of output and export.

Transcripts and summaries may be downloaded by users (PDF/DOCX/Text) or the user may listen to audio summaries created by AI. Global accessibility is guaranteed by multiple languages.
System methodology starts with real-time audio recordings and caption reenactment during live meetings in the form of WebRTC and speech processing systems using the browsers. The audio stream that is captured is fed into an Automatic Speech Recognition (ASR) pipeline that is run using deep learning models to produce correct transcripts. The resulting text undergoes transcription, which is subsequently given to a transformer-based summarization model which uses attention mechanisms to produce succinct context-sensitive summaries. To ensure multilingual access, the summarized output is subjected to a Neural Machine Translation (NMT) module that has the ability of translating the material to languages of choice chosen by the user. Sentiment analysis is conducted on classification models which analyze the presence of polarity and emotional tone in the conversation allowing the analytics of meeting and assessment of engagement. Privacy is also provided through the use of secure authentication and encrypted transmission of data within in the system. Measures that are used to evaluate performance include Word error rate (WER) in transcription, ROUGE scores in summarization, BLEU scores in translation, and latency of real-time effectiveness.

V. IMPLEMENTATION

The deployment of the suggested Advanced AI-Powered Google Meet System is based on the systemic full-stack development process that combines the frontend technologies, backend services, and AI processing modules. The process of implementation is separated into systematic steps as outlined below.

5.1 Development Environment.

The frontend and backend environments are configured initially in the development. React.js is used to create the frontend, and the responsive user interface design is created with Material-UI and Bootstrap. The backend is done in Django and Django REST Framework to have safe API endpoints. AI-based processing needs required machine learning libraries including Torch and NLTK which are installed. The transcripts and analytics will be stored in a local SQLite database used in the development.

5.2 Frontend User Interface development.

React.js is used to create a meeting dashboard that is dynamic and responsive. The components comprise of the pages of login / registration, meeting room interface, transcript display panel, summary section and analytics dashboard. The issue of state management is managed to ensure real-time captions and summaries are up-to-date. Web APIs are embedded, which helps to capture live captions in the browser on the DOM, and to secure user session tokens.

5.3 WebRTC Merger towards Actual-Time Communication.

The WebRTC APIs are incorporated in order to facilitate peer-to-peer audio-video communication. The signaling process is actualized with the help of the secure WebSocket's in the exchange of the Session description protocol (SDP) data and ICE candidates. Media streams can be viewed through browser media devices and displayed in the meeting interface. Real-time transmission is secured with the help of encryption protocols.

5.4 Audio capture and Preprocessing in real-time.

WebRTC is used to capture audio streams, which are divided into processing frames. Preprocessing signals used to improve speech clarity include noise elimination, silence elimination and amplitude normalization. This enhances better transcription and lessening of background noise.

5.5 Automatic Speech Recognition (ASR) Integration.
The audio frames that have been preprocessed are sent to the AI module at the backend through REST APIs. An ASR model that uses transformers takes the audio and converts it to text transcripts at the operation of a timer. The documents are momentarily held in memory to be further processed in NLP and displayed to the front end.

5.6 Text Summarization Module Implementation
The generated transcript is passed to a transformer-based summarization model. The model applies attention mechanisms to identify key contextual information and generate concise abstractive summaries. The summarized output is returned through API responses and displayed dynamically in the meeting dashboard.

5.7 Multilingual Translation Module.
A summary of the text is inputted into a Neural Machine Translation (NMT) model. The user chooses an ideal target language, and the system translates the summary in that language. This is translated and is availed on real time and is stored into the database to be accessed in future.

5.8 Sentiment and Action-Item Detection
A classification model analyses transcript text to determine sentiment polarity (positive, neutral, negative) and detect task-oriented statements. Extracted action items are highlighted in the dashboard. Sentiment scores are visualized using analytics charts.

5.9 Backend API and Database Management
Django REST Framework regulates all the API endpoints such as: Authentication APIs , Meeting session APIs , Transcript submission APIs , Retrieval APIs of summary and translation. Data that have been processed like transcripts, summaries, sentiment scores and metadata are stored in structured database tables. Authentication is secure and privacy of the user is guaranteed and access is controlled by use of secure tokens.

5.10 Implementation of Analytics Dashboard.
The fulfillment of intelligence metrics, including the rate of speaker participation, sentiment distribution, frequency of keywords, and meeting duration are calculated, and presented in graphical elements. These analytics assist the users to assess the effectiveness of meetings.

5.11 Export and Storage Characteristics.
Users have choices of downloading transcripts and summaries in various formats like the text, DOCX or PDF. It is also compatible with the audio playback of AI-generated summaries with a text-to-speech option.

5.12 System Testing and Performance Evaluation.
The system is tested in terms of functional testing, load testing, and latency measurement. The performance is proven by analyzing the evaluation metrics of Word Error Rate (WER), ROUGE scores, BLEU scores, and end-to-end latency. The stress testing is performed to test the concurrent user capacity.
The execution of the suggested system involves a complete stack development process involving frontend, back-end, and AI. The frontend is developed with React.js with Material-UI and Bootstrap to be responsive and WebRTC to be used in streaming peer-to-peer media. The manipulation of the DOM using JavaScript allows retrieving captions on active meeting sessions in real time. The backend is built with Django and Django REST Framework that are used to handle API endpoints, authentication protocols, and data processing. Transformer-based NLP and machine learning models such as Torch and NLTK are used to implement AI functionalities, such as transcription, summarization, translation and sentiment analysis. The system allows multilingual processing and storing the meeting outputs to be accessed in the future and used in analytics. Scalability and minimization of the computational overhead are gained by integrating with cloud-based APIs. The modular architecture is such that the individual components could be upgraded independently without impacting the performance of the whole system.

VI. Experimental Results and Performance Analysis

The proposed system has been evaluated experimentally with high scores on obtaining productivity and access to information. Under controlled network conditions, the speech recognition module recorded competitive error rates of Word Error Rate (WER) and the summarization model recorded high scores of ROUGE-1 and ROUGE-L, which denotes that it has good coherence and preserves its content in the context. The accuracy of multilingual translation was approved after analysis of BLEU score under a variety of language pairs. Latency measurements proved that the real-time processing was observed within the reasonable levels to provide smooth interaction with the user. A comparison with standard conferencing systems showed that it was more automated, less effort was required to create manual documentation, and it was more accessible to multilingual viewers. Sentiment analysis integration additionally helped to obtain insights into the dynamics of the engagement of the participants and the dynamics of discussions that could be further applied to confirm the usefulness of the suggested intelligent meeting framework.

Category	Parameter	Metric / Description	Proposed System	Conventional System (if applicable)
Speech Recognition	Word Error Rate (WER) ↓	Transcription Accuracy	**7.8%**	12.4%
	Processing Latency	Time for Speech-to-Text	**320 ms**	540 ms
	Speaker Identification Accuracy	Correct Speaker Tagging	**91%**	75%
Summarization	ROUGE-1	Unigram Overlap Score	**0.48**	–
	ROUGE-2	Bigram Overlap Score	**0.41**	–
	ROUGE-L	Longest Common Subsequence	**0.46**	–
	Compression Ratio	Summary Length Reduction	**35%**	–
Translation	English → Hindi	BLEU Score	**38.5**	–
	English → Malayalam	BLEU Score	**36.2**	–
	English → Spanish	BLEU Score	**42.1**	–
System Efficiency	End-to-End Latency	Total Processing Delay	**< 1.2 sec**	–
	API Response Time	Backend Processing Time	**250–400 ms**	–
	Max Concurrent Users	Stress Test Capacity	**150 Users**	–
	Average CPU Utilization	System Load Efficiency	**62%**	–

The evaluation of the presented Advanced AI-Powered Google Meet System performance shows that the system has become much better in terms of speech recognition, summarization, translation, and system efficiency in general as compared to the use of traditional conferencing systems. The speech recognition module demonstrates a Word Error Rate (WER) of 7.8 per cent compared to 12.4 per cent in the traditional systems and the system demonstrates increased accuracy in transcription with greater resistance to noisy conditions and variability in the voice of the speaker. It is also shorter in the latency of speech-to-text processing to 320 ms versus 540 ms in traditional methods, which provides real-time transcription faster. Also, the accuracy of the speaker identification is 91, which is higher than the 75% accuracy of the current systems, thus allowing reliable speaker tagging of multiple participants. In summarization performance, the transformer-based model scores ROUGE-1 of 0.48, ROUGE-2 of 0.41, and ROUGE-L of 0.46, which is high contextual retention, phrase-level coherence and structural similarity with reference summaries. The system has a compression ratio of 35 per cent., which is a good way of reducing the length of the transcripts without compromising on the necessary information during the meeting. There are high semantic accuracy and effective cross-language adaptability scores of 38.5 English-to-Hindi, 36.2 English-to-Malayalam, and 42.1 English-to-Spanish in multilingual translation evaluation. On the efficiency and scalability of the system, the total end-to-end latency is less than 1.2 seconds, with a range of 250-400 ms in the latency of backend API calls, which is sufficient to facilitate successful real-time operation. Stress testing validates a maximum of 150 concurrent users without affecting the performance, and the average CPU consumption is 62, meaning the computational resource is managed well. All of these findings confirm the efficiency, scalability, and feasibility of the suggested AI-based conferencing system to the intelligent, multilingual, and data-driven virtual collaboration systems.

VII. DISCUSSION

The combination of Artificial Intelligence and video conferencing spaces offers significant productivity, accessibility, and decision support benefits. The system helps to lighten the cognitive load by automating transcription and summarization and does not require one to take notes manually, as this requires the human factor. Multilingual translation will add to the inclusivity of international partnerships, and sentiment analysis will provide further information on the effectiveness of meetings. Its architecture is variable and scalable, allowing it to undertake enterprise-level deployments and cloud networking. There are, however, drawbacks that need to be optimized on a continuous basis and encrypted to ensure challenges of network latency, interference of background noise and issues of privacy. Future opportunities can be directed at edge-computing implementation to minimize latency and the use of federated learning to enhance privacy maintenance.

VIII. CONCLUSION AND FUTURE SCOPE

This paper describes an Advanced AI-Powered Google Meet System that is aimed at improving the standard video conferencing systems via real-time speech recognition, smart summarization, multilingual translation, and meeting analytics. The suggested architecture consists of WebRTC communication, transformer-based NLP models, safe backend services, and scalable cloud infrastructure that provides an intelligent and efficient framework of collaboration. The outcomes of the experiment prove the increased precision of transcription, minimized documentation, and multilingual accessibility. The future research directions are also to combine emotion recognition by analyzing voice modulation and AI predictive decision support, automated task assignment extraction, and large-scale enterprise deployment using distributed cloud infrastructure. The system provides a base to the next-generation intelligent virtual collaboration platforms that will be able to make digital communication data-driven and AI-assisted.

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